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# Measuring the Volatility of Wheat Futures Prices on the LIFFE

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## Abstract

Agricultural prices rose dramatically in 2007 and have subsequently fluctuated at high levels. This paper estimates the volatility of daily wheat futures prices on the Euronext/London International Financial Futures and Options Exchange for 1996-2012 using an exponential generalised autoregressive conditional heteroscedasticity model with a constant (price) elasticity of variance (CEV) and a broken trend. Results show that volatility is highly persistent; there is a structural break in volatility in June, 2007 when volatility rose by 10%; subsequently, the wheat futures price has become more volatile; and the CEV is 0.04.

**Keywords:** wheat futures price, volatility, EGARCH, constant elasticity of variance.

**JEL classifications:** Q02, C58.

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## 1. Introduction

Agricultural prices rose dramatically in 2007 after a period of relative stability and there is evidence that subsequent volatility is higher than previously (EC, 2009; Franks, 2010; Defra, 2010, p.21). Aside from short-run yield uncertainty caused by the weather, increasing risk from volatile product prices is perhaps the main concern of farmers. At the market level, as Pindyck (2001, 2004) argues, volatility affects the marginal value of storage, so when prices (and production and demand) are more volatile, the demand for stocks increases because higher stocks are required to smooth supply and reduce marketing costs. Increasing price volatility may therefore lead to higher stocks and higher spot prices. Critically, "Price volatility drives the demand for hedging [by farmers], whether it is done via financial instruments such as futures contracts or options, or via physical instruments such as inventories" (Pindyck, 2001). Price volatility is also important to policymakers in two respects. First, policymakers might be concerned about how market structure (between hedgers and speculators) influences price behaviour. In an efficient market, price reflects all information available, market participants have rational expectations and are risk-neutral, and the futures price is an unbiased estimator of the future spot price. It is therefore impossible to gain from speculation. However, if the market is inefficient and price deviates from its fundamental value, then gains (and losses) can be made from speculation, and an argument exists for regulatory action in futures markets (Antoniou *et al.*, 2005). Second, increasing volatility often leads to calls for agricultural policy intervention to stabilise prices.

Various factors have been put forward to explain both higher prices and increased volatility since 2007 (Cooke and Robles, 2009; Sumner, 2009; Gilbert and Morgan, 2010a, 2010b; Tangermann, 2011; Wright, 2011; Hadley and Crooks, 2012). Supply-side factors include high oil/fertiliser prices, low investment, export restrictions (particularly a cereals export ban by Russia in 2010), and adverse weather conditions including droughts in Australia in 2006 and 2007, a poor harvest in the US in 2010, and droughts in the US, Russia and the Ukraine in 2012. Policy shocks also impact on supply and of particular note is the decoupling of prices from production in the European Union since 2005. Demand-side factors include rising demand by emerging nations, especially China and India, increasing demand for biofuels, and declining global stocks. Explanations of increasing future price volatility include low stocks, increasing speculation, and the current financial crisis which started in 2008. Overall, there is no consensus about the relative weights of each explanation but increasing speculation is seen as important particularly from institutional investors which buy and sell groups of commodities and their derivatives as single financial instruments according to proprietary mathematical formulae, and they often dominate market open interest (Cooke and Robles, 2009; Gilbert, 2010a, 2010b; Gilbert and Morgan, 2010b; UNCTAD, 2011; Gutierrez; 2013). Gilbert (2010a) *inter alia* distinguishes between speculators and investors: speculators assess the risk and expected returns of a particular commodity futures in isolation; while investors do likewise but within an investment portfolio and positions are relatively long term and are predominantly long. Gilbert and Morgan (2010b) note a sharp increase in investment trading since the mid-2000s.

Against this background, this paper estimates the volatility of futures prices for feed wheat on the Euronext/London International Financial Futures and Options Exchange (LIFFE) and tests whether it has increased since 2007. Volatility is measured by time-varying variances in a generalised autoregressive conditional heteroscedasticity (GARCH) model and a broken trend is included in the variance equation to test the hypothesis that volatility has increased structurally. The paper is novel in two respects: first, Cox's (1975) constant elasticity of variance (CEV) model is entertained within an exponential GARCH (EGARCH) model to examine the impact of changes in the futures price on volatility; and second, the breakpoint in volatility is estimated whereas Gilbert and Morgan (2010a, 2010b) model a pre-determined change in the variance equation of their GARCH model in January, 2007. The paper is organised as follows: Section 2 provides some background, Section 3 explains the empirical methods, Section 4 discusses the data and results, and Section 5 concludes.

## **2. Some Background**

There is a voluminous literature on financial assets, and Garcia and Leuthold (2004) and Morgan *et al.* (2012) review studies of agricultural futures markets. These reviews are not replicated here but rather some key issues on volatility in agricultural futures markets are highlighted. One line of inquiry is the impact of new information, and there are two nested hypotheses. The "Samuelson (1965) effect" is where price volatility increases as time-to-maturity nears because price incorporates more and more information. This is a special case of the state variable hypothesis where price volatility depends on factors that influence supply and demand, and in particular the flow of information such as harvest forecasts (Anderson and Danthine,

1983). Support for both hypotheses is found *inter alia* by Hennessy and Wahl (1996) for US corn, soybean and wheat, and by Goodwin and Schnepf (2000) for US corn and wheat.

Attention has also focused on the volatility-price relationship since price proxies the determinants of supply and demand (Streeter and Tomek, 1992). Early work regressed time-varying variances on futures prices. Streeter and Tomek examine US soybeans and find positive and significant effects, but Kenyon *et al.* (1987) find mixed results with significant negative effects for US cattle and hogs and insignificant and positive effects for corn, soybean and wheat. Both regression and GARCH models are used by Hudson and Coble (1999) who find significant volatility-price relationships for US cotton where higher volatility is evident at both low and high prices as in a "volatility smile". Balcombe (2009) examines 19 world agricultural (spot) prices for 1962-2008 using Bayesian methods and finds strong persistent volatility but no evidence of a general increase in volatility. A similar result is found by Huchet-Bourdon (2011) who examines eight agricultural (spot) prices mainly in the US but also in New Zealand and Thailand for 1957-2010: from rolling-windows of standard deviations there is little evidence of trends in the volatilities although an exception is wheat whose volatility has trended upwards, and the increased volatility since 2006 is not exceptional relative to that in previous years.

Three further lines of inquiry are pertinent. First, Choi and Longstaff (1985) examine US soybeans and estimate log-linear volatility-price relationships each with a constant elasticity of variance (CEV) following Cox (1975). Volatility is calculated as monthly rolling standard deviations of daily returns and there is strong support for the CEV hypothesis with significant

elasticities between 2.19-2.51. Choi and Longstaff appears to be the only study of volatility-price relationships in agricultural futures markets which adopts the CEV model, although Geman and Shih (2009) find elasticities close to unity for the spot prices of crude oil, coal, gold, and copper.

A second line of inquiry is to test the hypothesis that agricultural price volatility has risen since 2007. Gilbert and Morgan (2010a, 2010b) examine 19 world spot prices for 1990-2009 using GARCH-X models where exogenously-determined shifters are included in variance equations from January, 2007, and results show only weak evidence of increased volatilities after 2007 and none for wheat. Karali and Power (2013) examine futures price volatilities of US corn, soybeans, wheat, live cattle and hogs using GARCH models for 1990-2005 and 2006-2009. Results for the earlier sample indicate that macroeconomic variables affect volatility whereas those for the latter show that commodity-specific factors are important, and for wheat a trade-weighted exchange index and inventories are significant.

A third line of inquiry is to examine the effect of speculation on volatility. Concern about speculation pre-dates futures markets and John Stuart Mill (1871, pp.276-277) argued that speculative merchants with good communications cause lower price fluctuations because excess demand in one place can be supplied from the surplus in another. On futures markets, speculators have no intention to take or make deliveries but rather they buy and sell contracts seeking to profit by predicting price changes, and their role is to assume hedgers' risks. Futures markets encourage speculation because of low transactions costs, trading on margin with associated leverage, the ease of closing out a position, and cash settlement rather than physical delivery

(Chau *et al.*, 2008). The contrary argument is that speculation increases volatility when speculation constitutes a large part of volume, and losses could accrue to some speculators if they adopt herd behaviour rather than use market information (Kaldor, 1960, Ch.1). Friedman (1953, p.175) distinguishes between rational and noise speculators. Rational speculators trade on fundamentals, stabilise markets, and reduce volatility although Ross (1989) argues that increasing speculation leads to increased information, prices therefore respond, and volatility increases. By contrast, noise speculators are irrational or erratic: they cause prices to deviate from fundamentals and volatility therefore increases. De Long *et al.* (1990) and Antoniou *et al.* (2005) argue that a particularly destabilising form of noise speculation is positive feedback trading where speculators buy when prices rise and sell when they fall, and strategies include extrapolative expectations, technical analysis, stop-loss orders, and portfolio insurance. When positive feedback trading occurs, herd behaviour by both noise and rational speculators may move price away from its fundamental value in the short run although it reverts when speculators liquidate their position. Situations when price is higher than fundamental value are temporary because speculators exploit arbitrage opportunities although arbitrage is not costless, and systematic mispricing may not be corrected when costs exceed benefits and may persist over time (Shleifer and Vishny, 1997). It is an empirical issue whether increasing speculation leads to higher or lower volatility. Streeter and Tomek (1992) find inverse relationships between speculation and price variability for US wheat, corn and soybeans but no evidence is found on US agricultural futures markets by Sanders and Irwin (2010), Irwin and Sanders (2012) and Irwin (2013). Gilbert (2010a) examines US corn and wheat futures prices for 2000-2009 and finds no evidence of a speculative bubble although there is stronger evidence for copper and



soybeans. More recently, Gilbert and Pfuderer (2014) examine US corn, soybeans, soybean oil and wheat and find that commodity index trading affects the soybean complex price in particular; such trading also appears to affect wheat prices though the evidence is weaker.

### **3. Empirical Method**

The data consist of daily futures prices. Returns are defined as  $r_t = [\ln P_t - \ln P_{t-1}] \times 100$ , where  $P_t$  is the futures price at time  $t$  and  $\ln$  is the natural logarithm. Daily volatility is not directly observable from daily returns because there is only one observation per day and it must be estimated. Here, returns are modelled in a GARCH framework and volatility is measured by time-varying variances. The empirical procedure consists of three steps: first, we examine the properties of returns; second, a breakpoint is estimated from simple time-varying variances of returns; and third, alternative GARCH models are estimated which are then compared.

In the first step, preliminary analysis is conducted on returns. A common assumption of a financial asset price is that its logarithm follows Brownian motion. This implies that returns have a zero mean and constant variance, are serially uncorrelated, and are independent and identically distributed normal variables, although often only the zero mean property holds. Since returns are often serially dependent, the calculation of simple statistics is not straightforward, and non-normal returns imply that standard measures of skewness and excess kurtosis and the Jarque-Bera (J-B) test for skewness and excess kurtosis are inappropriate. Accordingly, we use the McLeod and Li (1983) test,  $Q_{ML}$ , which is a more powerful modification of the Ljung-Box  $Q_{LB}$ -statistic (Greene, 2012, p.963) to examine serial dependence in squared returns. Conditional on

serial dependence, we calculate descriptive statistics and undertake tests of normality using heteroscedasticity and autocorrelation consistent (HAC) estimators. We also test both for unit roots following Phillips and Perron (1988) since stationary series permit models that are independent of a particular starting point, and for ARCH effects following Engle (1982).

In the second step, we test the hypothesis that volatility has increased and we seek to identify a single structural break in volatility which is anticipated to be in 2007. One solution is to estimate a simple GARCH model and examine the estimated variances for a break before incorporating it into a GARCH-X model, but the prior search for a break will impact on the critical values of hypothesis tests and the bias is unclear. Instead, time-varying variances are calculated from a rolling window of returns and we test for a breakpoint following Bai and Perron (1998, 2003).

In the third step, we estimate alternative GARCH models. As a benchmark, we estimate the GARCH(1,1) model of Bollerslev (1986):

$$r_t = \mu_0 + \varepsilon_t \quad t=1, \dots, n \quad (1)$$

$$h_t = \omega_0 + \alpha \cdot \varepsilon_{t-1}^2 + \beta \cdot h_{t-1} \quad (2)$$

where  $\varepsilon_t$  are errors which are dependent on past information,  $h_t$  are time-varying conditional variances of  $r_t$ , and  $\omega_0 > 0$ ,  $\alpha \geq 0$ ,  $\beta \geq 0$  and  $\alpha + \beta \leq 1$ . The error term,  $\varepsilon_t$ , is often assumed to follow a standard normal distribution but if fat tails exist, a Student t-distribution can be used (Bollerslev, 1987). Autoregressive terms may be added to (1) if autocorrelation exists. Implied time-varying

volatilities are given by the estimates,  $\hat{h}_t$ . Most financial returns can be modelled adequately by this GARCH(1,1) model and it is unnecessary to include higher-order terms in  $\varepsilon_{t-1}^2$  and  $h_{t-1}$  in (2).

The GARCH model in (1) and (2) is extended in two directions. First, a GARCH-X model is specified where a broken trend is included in the variance equation to model the structural break identified in the second step. Thus the variance equation becomes:

$$h_t = \omega_0 + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \omega_1 D_t + \delta_0 t + \delta_1 (D_t \cdot t) \quad t=1, \dots, n \quad (3)$$

where  $D_t=0$  for  $t < T_b$  and  $=1$  for  $t \geq T_b$ , and  $T_b$  is the breakpoint.<sup>2</sup> Second, we adopt Cox's (1975) constant elasticity of variance (CEV) model where volatility is assumed to be determined by the contemporaneous price. The CEV model can be written as  $h_t = c \cdot P_t^\gamma$  where  $c$  is a constant and  $\gamma$  is the CEV. To maintain consistency with the CEV model, the EGARCH model of Nelson (1991) is adopted and the variance is modelled as:

$$\ln h_t = \omega_0 + \alpha \frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \beta \ln h_{t-1} + \omega_1 D_t + \delta_0 t + \delta_1 (D_t \cdot t) + \gamma \ln P_t. \quad (4)$$

A sufficient condition for stationarity where the volatility process is stable is that  $|\beta| < 1$ . Volatility clustering following exogenous shocks is measured by  $\alpha$  which captures the magnitude of volatility by linking current volatility and past shocks. If  $\alpha > 0$ , large shocks, whether positive or negative, are followed by large changes in volatility.

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<sup>2</sup> Gilbert and Morgan (2010a, 2010b) include only a shifter in the variance equation, that is  $\omega_1 D_t$  in (3), which takes a value of unity after January, 2007 and zero beforehand.

In the GARCH variance equations in (2) and (3),  $(\alpha+\beta)$  measures the speed of mean reversion to its long-run level. The half-life of a volatility shock is a popular measure of persistence (Engle and Bollerslev, 1986) and for (2) and (3) is defined as  $\ln(0.5)/\ln(\alpha+\beta)$  which is the number of periods required for a shock to dissipate by half. The closer  $(\alpha+\beta)$  is to unity, the longer is the half-life; and if  $(\alpha+\beta)>1$ , the model is non-stationary and volatility is explosive. In the EGARCH variance equation in (4), volatility persistence is captured by  $\beta$  alone and the half-life of a volatility shock is  $\ln(0.5)/\ln(\beta)$  (Nelson, 1991).

To estimate all models, the log-likelihood is maximised using the Broyden-Fletcher-Goldfarb-Shanno algorithm. Mis-specification tests examine the properties of standardised residuals (Bera and Higgins, 1993) which are defined as  $\hat{\varepsilon}_t^* = \hat{\varepsilon}_t / \sqrt{\hat{h}_t}$  where  $\hat{\varepsilon}_t^* \sim N(0,1)$ , and if the model is specified correctly,  $\hat{\varepsilon}_t^*$  is white noise. If diagnostic tests for non-normal standardised residuals are significant, as indicated by measures of skewness, excess kurtosis and the J-B statistic (Greene, 2012, pp.317, 1058), the t-distribution with shape parameter,  $v$ , is used to model the error term,  $\varepsilon_t$ , and  $v>2$  since the t-distribution has no variance otherwise. We test for serial correlation using the standard  $Q_{LB}$ -test and for ARCH effects using the  $Q_{ML}$ -test. We also use Nyblom's (1989) joint fluctuations test to test the null that all parameters are stable against the alternative that they are not.

Finally, we compare the estimated GARCH models by examining the accuracy of one-step ahead, within-sample forecasts. One year's data are held back and each model is estimated for  $t=1, \dots, n-m$  where  $m$  is the number of observations in the final year of the sample. A one-step

ahead forecast is estimated for  $t=n-m+1$  using (2), (3) or (4) (Tsay, 2010, pp.133, 147-148). Each model is then estimated sequentially, rolling out the sample one observation at a time to  $t=1, \dots, n-1$  which produces a forecast for  $t=n$ . Forecasts are thus generated for  $t=n-m+1, \dots, n$  and they are compared with realised volatility which is proxied by  $r_t^2$  (Harris and Sollis, 2003, p.245). The GARCH models in (2) and (3) are nested and we follow Clark and McCracken (2001) to test between them where the null is forecast encompassing and the alternative is that forecasts from one model carry information not contained in those from the other. The test statistic has a non-standard distribution and Clark and McCracken provide asymptotic critical values. GARCH and EGARCH models are non-nested and we use Diebold and Mariano's (1995) test where the null is of equal forecast accuracy between pairwise forecasts, that is the mean square error (MSE) is equal between two sets of forecasts, and the alternative is that one set of forecasts is better than the other. The test statistic has an asymptotic standard normal distribution.

#### **4. Data and Results**

The construction of a futures price series is not straightforward because a number of contracts are open simultaneously and there are a similar number of prices which correspond to any day. A simple solution is to select the price of the contract nearest to maturity, but jumps sometimes occur in such nearby price series around contract expiry dates. However, jumps can also occur in series created by other procedures, such as volume crossover where price switches to the contract with the highest volume, volume threshold where the contract closest to expiry is used until its volume falls to a specified threshold level, and fixed date before expiry. Carchano and Pardo (2009) examine stock index futures contracts and results show no significant

differences between futures prices constructed with alternative rollover dates, and they recommend the use of nearby prices. We follow this recommendation and note that some others also use nearby futures prices including Morgan *et al.* (2012) Sanders and Irwin (2010, 2011) and Irwin (2013).

Our sample contains daily futures prices (£/tonne) for feed wheat on the LIFFE for 1 October, 1996 to 28 September, 2012 (4051 observations).<sup>3</sup> Price and returns are illustrated in Figure 1 and descriptive statistics are shown in Table 1. The minimum price is £56/tonne in August, 2002 and the maximum is £218/tonne in April, 2011. Prices were relatively low and stable before 2007 but they fluctuated at generally higher levels thereafter. The standard deviation of returns is 1.3% per day. Returns are typical of financial asset returns which are generally stable but with occasional large changes.

**Figure 1 about here**

**Table 1 about here**

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<sup>3</sup> Contract requirements are that the trading unit is 100 tonnes, the origin is EU, the grain is in good condition and does not contain more than 3% heat damage, natural weight is less than 72.5 kg/hectolitre, and moisture does not exceed 15%. Delivery months are January, March, May, July, September, and November with 10 delivery months available for trading. Last trading days are the 23rd calendar day for January, March, May, and November contracts, and the 7th calendar day for July contracts. Helen Plant (Home Grown Cereals Authority) kindly provided these data.

In our sample of daily futures prices for 16 crop years, there are 96 contract expiry dates. Any jumps in price upon contract expiry are also shown by one-day spikes in returns and these may cause estimation bias. To allay such fears, we examine returns for each day after contract expiry. Of the 184 returns that exceed two standard deviations from the mean, only 23 coincide with contract expiry; and of 12 that exceed five standard deviations, only six follow contract expiry. Of the latter, four are for the July contracts in 2004, 2009, 2010, 2012, and two are for contracts in May, 2004 and January, 2009.<sup>4</sup> In absolute terms, the largest daily change in returns following contract expiry is 13% while that for the whole sample is 17%. It seems reasonable to conclude therefore that any estimation bias from contract expiry price jumps is negligible.

We now examine the statistical properties of returns. The mean return is insignificantly different from zero. Measures of skewness and/or (excess) kurtosis imply that both prices and returns are non-normal; and Phillips and Perron (1988) unit root tests imply that prices are I(1) and returns are stationary.<sup>5</sup> McLeod and Li (1983)  $Q_{ML}$ -statistics show serial correlation in returns at lags up to around 60 days. These properties are not atypical of asset returns elsewhere.

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<sup>4</sup> The choice of five standard deviations is somewhat arbitrary but it seems reasonable since the maximum and minimum returns are 13 and 10 standard deviations away from the mean.

<sup>5</sup> In each Phillips and Perron test, the lag window is  $12(n/100)^{0.25}=30$  (Schwert, 1989), a trend is insignificant, and a constant is the only deterministic component.

Second, we estimate non-parametric variances using a rolling window of 60 days and test for a breakpoint following Bai and Perron (1998, 2003). A break is evident on 28 June, 2007 and the 95% confidence interval covers the period from 14 November, 2006 to 20 July, 2007.<sup>6,7</sup> Table 1 also shows descriptive statistics for price and returns both before and after the break. Beforehand, price ranges between £56-116/tonne whereas afterwards it ranges between £88-218/tonne; between the two periods, the mean price almost doubles from £77/tonne to £145/tonne as does its standard deviation; and the standard deviation of returns increases by almost 50%.

Third, we estimate volatility using GARCH models. Prior to this, we conduct three preliminary tests. First, in the mean equation in (1) which is common to all GARCH/EGARCH models, estimates of partial autocorrelations for 1-10 lags indicate that one lag is preferred using the Schwarz Bayesian Criterion (SBC). Second, since these models assume white noise residuals in (1), we test the null of no serial correlation and McLeod and Li tests yield:  $Q_{ML}(10)=24.92$  [p-value: 0.01];  $Q_{ML}(60)=77.31$  [0.07]; and  $Q_{ML}(126)=95.77$  [0.98], and serial correlation occurs at lags up to 60 days. By contrast, West and Cho modified Ljung-Box ( $Q_{WC}$ ) tests reject nulls at all lags:  $Q_{WC}(10)=6.96$  [0.73];  $Q_{WC}(60)=64.25$  [0.33]; and  $Q_{WC}(126)=127.01$  [0.46]. Overall, there appears sufficient evidence to suggest that serial correlation is absent. Third, the nulls of no

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<sup>6</sup> This break does not coincide with contract expiry.

<sup>7</sup> These confidence intervals are asymmetric because the variance of the error term in the test regression is different before and after the break.



ARCH effects (Engle, 1982) are rejected at all orders up to 10 where  $\chi^2_{10}=2.14$  [0.02], and GARCH models appear appropriate to model feed wheat returns.

GARCH/EGARCH model estimates are shown in Table 2. Diagnostic tests for normality, serial correlation and ARCH effects are applied to the standardised residuals,  $\hat{\varepsilon}_t^*$ . In the GARCH model with normal errors, there is significant non-normality as implied by measures of kurtosis, skewness and the J-B test, and the standardised residuals have some extreme values. Accordingly, the GARCH model is re-estimated with t-errors and the shape parameter,  $\nu$ , is significant.<sup>8</sup> The GARCH-X model includes a broken trend in the variance; it has a higher log-likelihood but the parameters relating to the broken trend are insignificant. By contrast, the EGARCH-X model, again with a significant  $\nu$ -parameter, provides evidence of a broken trend in the variance and has the highest log-likelihood. Further support for the EGARCH-X model is provided by the SBC, and by Nyblom's (1989) joint fluctuations tests which show that the parameters in the two GARCH models are not constant whereas those in the GARCH-X and EGARCH-X models are stable.<sup>9</sup> For all models,  $Q_{LB}$ -tests indicate the absence of serial correlation, and  $Q_{ML}$ -tests imply no remaining ARCH effects.

**Table 2 about here**

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<sup>8</sup> We also test for a breakpoint in the variances of the two GARCH models following Bai and Perron (1998, 2003), and a break is evident on 26 June, 2007 in both cases.

<sup>9</sup> For these latter two models, Nyblom's tests further allay fears of price jumps at contract expiry.

Finally, we compare the estimated models using within-sample, one-step ahead variance forecasts which are compared with  $r_t^2$  for 3 October, 2011 to 28 September, 2012. Results show that the MSE is smallest for the EGARCH-X model. Further and following Clark and McCracken (2001), we test the null of forecast encompassing between the nested models, that is, between the GARCH model with normal errors and that with t-errors, and between the GARCH and GARCH-X models both with t-errors. Respective test statistics are 0.13 (critical value: 1.08) and 2.66 (1.48), and the GARCH-X model carries information that is not contained in the forecasts of the GARCH model with t-errors. Following Diebold and Mariano (1995), we also test between the non-nested GARCH-X and EGARCH-X models: the test statistic is 2.07 (p-value: 0.02) and the latter has a superior forecasting ability. Overall, there is considerable evidence that the EGARCH-X model with t-errors best fits the data.<sup>10</sup>

In the preferred EGARCH-X model, the constant in the mean equation is insignificant as expected. In the variance equation, both  $\alpha$ - and  $\beta$ -coefficients are significant and GARCH effects are present. Since  $\alpha > 0$ , large shocks are followed by large changes in volatility and there is significant volatility clustering. Since  $|\beta| < 1$ , the volatility process is stable. In common with most other analyses of financial assets, the estimate of the autoregressive component,  $\beta$ , is high which implies that volatility persistence is high and the variance moves slowly through time: the half-life of a volatility shock is 18 trading days. The CEV of returns with respect to price is 0.04 and a 1% increase in the futures price leads to a 0.04% increase in volatility. The variance of returns is

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<sup>10</sup> Following Glosten *et al.* (1993), there is no evidence of asymmetry in the EGARCH-X model.

shown in Figure 2 and the vertical line denotes the break on 28 June, 2007 when volatility increased by 9.54%. Average daily variance increased from 1.13% before the break to 2.66% thereafter (or by 135%). There is no underlying trend in volatility before the break, but thereafter volatility trended downwards by -0.003% per day or by -0.65% per year (assuming 252 trading days/year).

**Figure 2 about here**

## **5. Discussion and Conclusion**

World agricultural prices were relatively stable in the decade prior to the mid-2000s but they rose substantially in 2007. This paper estimates the volatility of daily feed wheat futures prices on the LIFFE for 1996-2012 and a key aim is to examine whether volatility increased significantly around 2007. Our empirical method has two components: first, we calculate non-parametric, time-varying variances and test for a structural break; and second, we estimate volatility using GARCH models. The preferred model is an EGARCH-X model where the variance equation contains a broken trend and its relationship with price is modelled by a constant elasticity.

There are three results. First, volatility increased significantly in June, 2007 which is later than the consensus in previous studies of late-2006 or early-2007. In the preferred EGARCH-X model, average daily volatility more than doubled from 1.13% before June, 2007 to 2.66% thereafter. This result supports the state variable hypothesis where information, for example on the poor harvest in 2007, increases volatility. It also supports Franks (2010) who finds that the

variability of both the price index of all UK agricultural products and that of cereals rose substantially between 2001/4 and 2005/8, and Huchet-Bourdon (2011) who finds that US spot wheat prices became more volatile after 2006. However, our result contrasts with Gilbert and Morgan (2010a, 2010b) who find no significant increase in the volatilities of world agricultural spot prices in January, 2007, although they impose a structural break in volatility *ex ante* in January, 2007 and they do not allow price to affect volatility. Second, the futures price significantly determines volatility, which supports the CEV model and substantiates the conclusions of Choi and Longstaff (1985) and Streeter and Tomek (1992). Our estimated CEV is 0.04, and a 1% increase in the futures price leads to a 0.04% increase in volatility. This is substantially smaller than the elasticities found by Choi and Longstaff because of differences in empirical methodology, application, and sample. Third, volatility is stable and highly persistent and the half-life of a volatility shock is 18 trading days. The increase in volatility since June, 2007 appears not to be short-lived, and it is reasonable to suppose that this increase generalises to agricultural futures and spot markets elsewhere.

The results have three implications. First, higher price risk may lead farmers, traders, input supply firms and food processors to implement better financial management strategies which include the use of futures and options, insurance, storage, and diversification or collaboration to share costs (Defra, 2010, p.94). While hedging can be used by farmers to manage price risk, agricultural futures market coverage in the UK is incomplete, and only feed wheat and sugar contracts are traded on the LIFFE for indigenous products. The other futures markets of particular interest to UK farmers are the Marché à Terme International de France

(MATIF) in Paris which trades futures on milling wheat, malting barley, rapeseed and corn, and the European Exchange (EUREX) in Eschborn, Germany which trades futures on potatoes for the British market. Hedging on foreign futures markets involves exchange rate uncertainty which mitigates against its use and may require separate exchange rate hedging. UK farmers in general currently hedge little and a lack of awareness and knowledge are constraints to more widespread use (Defra, 2010, p.95).<sup>11</sup> There are no government policies or programmes to manage crop risk; and while private insurance for hail is available, no cover exists for price or yield risks.<sup>12</sup> On the other hand, buyers - traders, input supply firms and food processors - do hedge and competition forces them to pass at least part of the benefit back to the producer, and increased costs of hedging (due to increased volatilities) can be expected to be passed back to farmers and upwards to consumers.

The second implication concerns the finding that the volatility of wheat futures prices on the LIFFE increased substantially in June, 2007. Shocks to supply or demand have been identified elsewhere as possible reasons for increasing price volatility. On the supply-side, these include high oil/fertiliser prices, low investment, export restrictions, adverse weather conditions, and price decoupling in Europe in 2005; while on the demand-side, they include rising demand by emerging nations, increasing demand for biofuels, and declining global stocks. Speculation is

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<sup>11</sup> Further, the current premium for options is high at about £10/tonne and they are rarely used.

<sup>12</sup> The UK government compensates farmers for the compulsory slaughter of animals with specific infectious diseases. Private insurance cover for some diseases is also available.

also seen as a major determinant of price volatility. The traditional view is that speculation reduces price volatility because speculators buy low and sell high (Gilbert and Morgan, 2010b). Evidence of increasing speculation might be increasing volume. Average annual wheat volume on the LIFFE before the crop year 2006/7 was 92,000 and it was lowest in 2006 at 62,000; after 2007/8, average volume increased by 47% to 135,000 peaking in 2011/12 at 173,000.<sup>13</sup> However, the supply of futures contracts is not constrained and their number is unlimited so increased volumes may not be because of increased speculation but may be caused by more hedging. By contrast, increasing speculation from destabilising noise trading and herd behaviour may lead to higher volatility which implies that speculation has become more risky although increased risk generally implies a greater potential gain. Excessive speculation may call for internationally coordinated regulations but the functioning of futures markets should not be inhibited because speculators provide liquidity and manage risk. In addition, futures markets are interdependent and there were price rises elsewhere in 2007: for example, the price of wheat futures on the Chicago Board of Trade increased by 67% between 2 June and 1 October, 2007 from 570-953 cents/bushel. Overall, the effects of increased speculation on volatility is unclear: most empirical studies find that the relationship is either weak or absent (Gilbert, 2010a; Sanders and Irwin, 2010; Sanders and Irwin, 2011; Irwin and Sanders, 2012; Irwin, 2013) although Gilbert and Pfuderer (2014) provide some contrary evidence.

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<sup>13</sup> A (monthly) breakdown of open interest is only available since 2011 and a formal test of the effects of speculation on the LIFFE wheat futures market is not yet feasible.

Third, increasing agricultural price volatility on international markets has policy implications. Focussing on developed countries, there is an array of both international and national supply-side policy instruments available (Defra, 2010, pp.76-88; Tangermann, 2011, pp.40-67). At the international level, buffer stocks could be established by cross-country collaboration to maintain strategic reserves and promote food security. These stocks could be released onto the market when a price spike is forming but it is difficult to identify appropriate price triggers. Moreover, buffer stocks are costly and could crowd-out private stock-holding, they may lead to lower supply response, and they may move futures prices away from fundamentals. Similar problems also exist with virtual reserves where there is a commitment by countries to supply grain for intervention on futures markets to discourage excessive speculation. At the national level, import tariffs/subsidies, export restrictions and export taxes could be used to insulate domestic markets either partially or fully, and the aim is to protect domestic markets against price volatility on international markets. A likely effect however is to increase price volatility as international markets fragment and become less liquid, and the problem is exported to other countries. Conversely, trade liberalisation and the promotion of efficient resource use tend to reduce price volatility as farmers benefit from respective comparative advantages. Price control or administered prices backed by intervention stores could also be used to address price volatility, but such policies undermine market mechanisms and domestic market intervention may be costly if arbitrage in international markets is to be avoided. National buffer stocks suffer from the same problems as those at the international level although more efficient use could stem from countries sharing information. Governments could also buy call options from biofuels producers to divert grain from biofuels to food when prices are deemed too high. While stable

international commodity prices are a global public good, there are attendant free-rider problems and it is not surprising that policy responses to price volatility are not encouraging. As Tangermann (2011, p.78) concludes, "There is no effective way of doing much about price behaviour on world markets for agricultural commodities. These markets will continue to exhibit volatility ... and there is no policy recipe against that malady."



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**Table 1: Descriptive Statistics and Univariate Tests**

	Price (£/tonne)	Returns (%)
<i>Full Sample</i>		
Mean	99.45 [0.00]	0.02 [0.45]
Standard Deviation	39.55 [0.00]	1.32 [0.00]
Minimum	56.35	-17.19
Maximum	217.50	13.35
Skewness	1.25 [0.00]	-0.61 [0.35]
Excess Kurtosis	0.38 [0.30]	18.01 [0.00]
Phillips and Perron Test	-0.49	-59.95
Q <sub>ML</sub> (10)	-	24.23 [0.01]
Q <sub>ML</sub> (60)	-	77.55 [0.05]
Q <sub>ML</sub> (126)	-	98.99 [0.96]
ARCH(10)-test	-	2.14 [0.02]
<i>Before June, 2007</i>		
Mean	76.89 [0.00]	0.00 [0.92]
Standard Deviation	12.12 [0.00]	1.12 [0.00]
Minimum	56.35	-17.19
Maximum	115.50	5.48
<i>After June, 2007</i>		
Mean	145.28 [0.00]	0.05 [0.35]
Standard Deviation	36.20 [0.00]	1.66 [0.00]
Minimum	87.50	-10.60
Maximum	217.50	13.35

Notes: 1. HAC p-values in square brackets.

2. The null for the Q<sub>ML</sub>-test is of no serial correlation and there is no need to allow for autocorrelation.

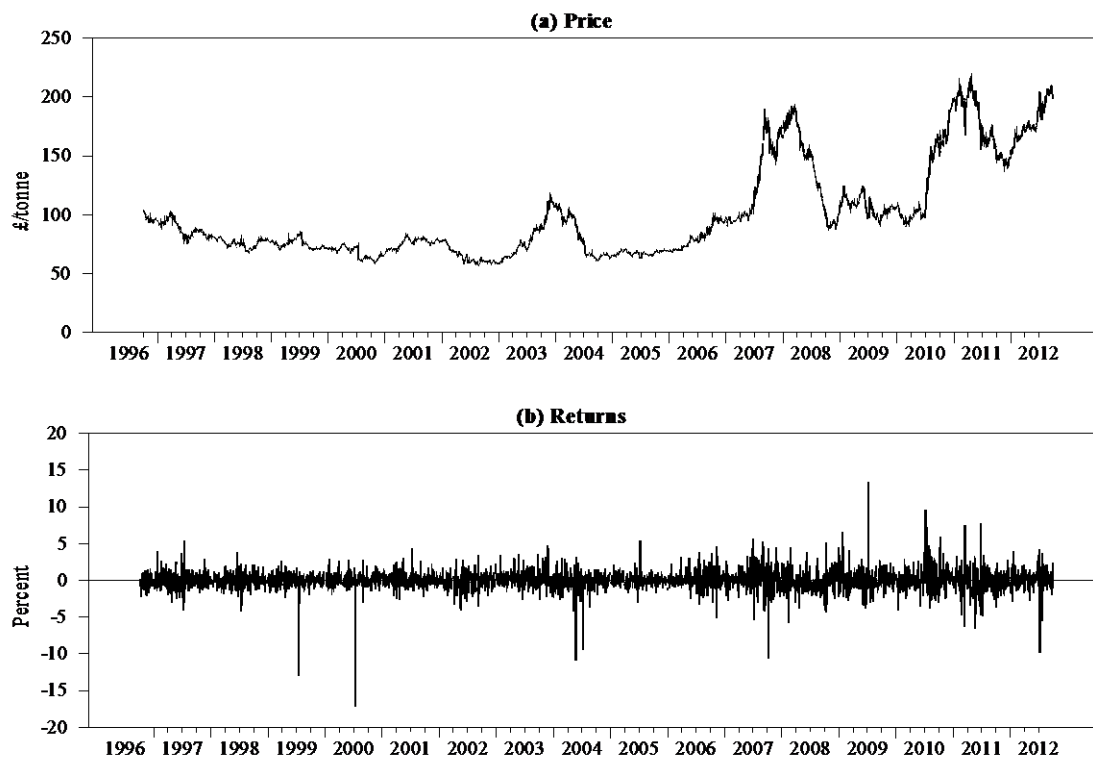
3. The critical value for the Phillips and Perron test statistic at the 5% significance level is -2.86.

**Table 2: GARCH Results**

	GARCH Normal Errors	GARCH t-errors	GARCH-X t-errors	EGARCH-X t-errors
<i>Mean Equation:</i> $r_t = \mu_0 + \mu_1 r_{t-1} + \varepsilon_t$				
$\mu_0$	0.003 (0.13)	-0.006 (0.46)	-0.006 (0.40)	-0.006 (0.43)
$\mu_1$	0.082 (4.42)	0.093 (5.26)	0.097 (6.21)	0.088 (6.04)
<i>Variance Eqn:</i> GARCH: $h_t = \omega_0 + \alpha \varepsilon_{t-1}^2 + \beta \cdot h_{t-1}$				
GARCH-X: $h_t = \omega_0 + \alpha \varepsilon_{t-1}^2 + \beta \cdot h_{t-1} + \omega_1 \cdot D_t + \delta_0 \cdot t + \delta_1 \cdot D_t$				
EGARCH-X: $\ln h_t = \omega_0 + \alpha \frac{ \varepsilon_{t-1} }{\sqrt{h_{t-1}}} + \beta \cdot \ln h_{t-1} + \omega_1 \cdot D_t + \delta_0 \cdot t + \delta_1 (D_t \cdot t) + \gamma \cdot \ln P_t$				
$\omega_0$	0.059 (6.28)	0.055 (3.54)	0.119 (3.35)	-0.249 (3.55)
$\alpha$	0.059 (7.95)	0.084 (4.82)	0.098 (4.53)	0.115 (7.00)
$\beta$	0.911 (87.83)	0.886 (39.62)	0.815 (19.73)	0.963 (104.69)
$\omega_1$	-	-	0.452 (1.96)	0.091 (2.46)
$\delta_0$	-	-	-0.00001 (1.16)	0.000001 (0.43)
$\delta_1$	-	-	-0.0001 (1.44)	-0.00003 (2.27)
$\gamma$	-	-	-	0.039 (2.57)
$\nu$	-	4.048 (15.35)	4.100 (14.97)	4.208 (15.14)
Log-likelihood	-6659.18	-6147.14	-6126.19	-6096.91
SBC	13359.88	12344.12	12327.13	12276.89
Skewness	-1.67 [0.00]	-1.89 [0.00]	-2.02 [0.00]	-2.06 [0.00]
Kurtosis	35.60 [0.00]	38.59 [0.00]	39.67 [0.00]	43.06 [0.00]
JB-Test	192289.73 [0.00]	253647.51 [0.00]	268316.83 [0.00]	315664.55 [0.00]
$Q_{LB}(10)$	9.21 [0.42]	8.63 [0.47]	8.20 [0.51]	8.02 [0.53]
$Q_{ML}(10)$	1.06 [0.99]	1.38 [0.99]	1.39 [0.99]	0.99 [0.99]
Nyblom's Test	1.74 [0.02]	2.96 [0.00]	2.08 [0.11]	2.37 [0.08]
MSE	45.48	45.50	46.45	45.15

Notes: 1. t-statistics in parentheses.  
2. p-values in square brackets.



**Figure 1: Data**

**Figure 2: Estimated Volatility from EGARCH-X Model with t-errors**